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Sensing Group Proximity Dynamics of Firefighting Teams using Smartphones

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ABSTRACT
Firefighters work in dangerous and unfamiliar situations under a high degree of time pressure and thus team work is of utmost importance. Relying on trained automatisms, firefighters coordinate their actions implicitly by observing the actions of their team members. To support training instructors with objective mission data, we aim to automatically detect when a firefighter is in-sight with other firefighters and to visualize the proximity dynamics of firefighting missions. In our approach, we equip firefighters with smartphones and use the built-in ANT protocol, a low-power communication radio, to measure proximity to other firefighters. In a second step, we cluster the proximity data to detect moving sub-groups. To evaluate our method, we recorded proximity data of 16 professional firefighting teams performing a real-life training scenario. We manually labeled six training sessions, involving 51 firefighters, to obtain 79 minutes of ground truth data. On average, our algorithm assigns each group member to the correct ground truth cluster with 80% accuracy. Considering height information derived from atmospheric pressure signals increases group assignment accuracy to 95%.

Author Keywords
mobile sensing; radio-based proximity; group clustering; firefighting

ACM Classification Keywords
H.1.2 User/Machine Systems; H.3.4 Systems and Software: Distributed systems; J.4 Social and Behavioral Sciences

INTRODUCTION
During firefighting missions each firefighter fulfills a specific function and relies on his peers. Firefighting teams usually split into sub-groups to work in parallel on different tasks. Depending on mission complexity and the commander's strategy, these sub-groups are more or less stable and can merge and split again at any time. As the whole firefighting team works towards a common goal, it is crucial that the sub-groups coordinate their actions. However, coordination between members of different sub-groups is complicated by the fact that they might not be in visual contact.

Wearable computing can provide details on these group dynamics by automatically measuring how group structure changes during a mission. A graphical representation of who was when in close proximity to whom illustrates mission development over time allowing instructors to pinpoint possible coordination problems, which can be addressed in further trainings.

In this paper, we present a methodology to measure and visualize group proximity dynamics of firefighting teams. Using the built-in ANT[1] radio of smartphones, we scan nearby devices fast and efficiently in order to detect sub-groups based on the measured proximity. In particular, we make the following contributions:

1. We investigate the use of the low-power ANT radio to measure proximity between individuals and detail our search strategy to detect nearby devices. Further, we characterize discovery time and search distance.
2. We present a methodology to cluster moving sub-groups within action teams using ANT-based proximity information and extend the approach to also incorporate height information derived from atmospheric pressure signals.
3. For an easy understanding of group dynamics, we visualize the group clusters over time in form of narrative charts which represent who was when in a sub-group with whom.
4. We evaluate our group clustering algorithms in real-world firefighting training sessions and compare the results to manually annotated ground truth. We further show, how a firefighting training mission evolves over time and highlight important steps of the mission.

Related Work
Several research projects funded by the European Union aimed at supporting and increasing work safety of firefighters.

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[1] `www.thisisant.com`

The ProeTEX project [3] developed a smart textile to monitor the physiological status of firefighters. To support tactical navigation under poor visibility, a beacon based relative positioning system was proposed during the wearIT@work project [5]. To better integrate current practices of firefighting brigades the approach was adapted in the ProFiTex project [4] and resulted in a Smart Lifeline which enabled relative positioning. The NIST Smart Firefighting Project [2] combines smart building technology, smart firefighter equipment and robotics. Like in previous projects the aim is to provide real-time information on firefighter location, firefighter vital signs, and environmental conditions. The Fire Information and Rescue Equipment project [1] at UC Berkeley combined wireless sensor networks (WSN) and head-mounted displays to support firefighters. A pre-installed WSN enabled room-level localisation of emergency responders within a building [15]. The benefits and drawbacks of preinstalled location systems, wireless sensor systems and inertial tracking systems for emergency responders were compared in [8].

In contrast to the above systems, we focus on group proximity rather than on localisation to capture mission development and team activity. Our primary goal is to support post incident feedback with objective mission data. Although previous system prototypes were tested in simulated scenarios none of them were used in real-world trainings. In this paper, we deploy and evaluate our method in real-world training sessions.

In the data mining community spatial-temporal data is mined for moving objects by clustering methods which combine time and location information [11, 10, 9]. Kalnis et al. [10], split trajectory data in time slices and used a density based clustering method to group close objects. Similar clusters found in consecutive time slices were then considered as a moving cluster of objects. In previous work [16], we have extended the approach to handle noisy data and applied the clustering method to GPS-trajectories of people walking in groups through a city.

In the field of reality mining, the works by Eagle and Pentland have first explored the use of the mobile phone to measure proximity to others using repeated Bluetooth scans [7]. They showed that communities and daily routines of persons can be identified from Bluetooth proximity networks. More recent work, discovered human interactions from proximity networks using topic models [6]. In both approaches, the measured interaction data is aggregated in time slices of at least 10 min duration and thus the discovered patterns are on an even larger time scale.

Contrary to previous work, we use the low-power ANT protocol to scan for nearby devices. This allows us to detect devices in close proximity much faster, usually in less than 600 ms compared to 30 s of a typical Bluetooth scan. This increased time resolution by a factor of up to 50 enables us to measure how groups of firefighters split and merge during a mission in real-time.

ANT-BASED PROXIMITY

ANT, similar to Bluetooth Low Energy, is an ultra low-power, low bandwidth wireless protocol which operates in the 2.4 GHz range. Contrary to Bluetooth Low Energy it allows a node to be master and slave at the same time and thus supports many network configurations. Currently, ANT is most used in fitness devices such as chest-belts and pedometers. ANT chips support up to eight logical channels on one physical 2.4 GHz radio link using time division multiplexing. Each ANT channel is identified by a tuple of network ID, type ID and device ID. Configuring a channel includes setting the ID, the frequency and the period.

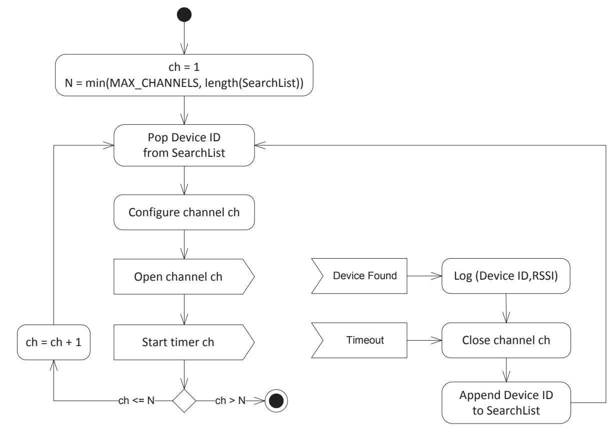

Figure 1. Implemented list search to discover nearby devices.

Search Strategy

ANT offers different strategies to discover other devices: one can search a device with a known ID, search for devices which match certain properties, e.g. are of particular type, search near devices using proximity search and one can utilize background searches. However, because the ANT chip included in our Sony Xperia Active phones did not support proximity nor background search mode, we implemented a list search strategy. On each device one master channel constantly transmits a device ID with a specified period and seven slave channels are used to search in parallel for devices specified in a search list. In Figure 1 the search strategy is presented in form of an UML Activity Diagram. Given a list of devices to search for, the first device ID is popped from the list, a slave channel with the desired device ID is opened and a search timer is started. In case that a device is found or the search times out, the channel is closed, the device ID is appended at the end of the list, the next device ID is popped from the list and the channel is reopened. In case that the device is found, the received signal strength indicator (RSSI) is saved.

The implemented list search is a simple device discovery strategy. It is robust, as the search result of one device is independent of the search results of other devices. But the search strategy does not scale to a large search list as it takes time to find all devices before a device can be searched again. To handle large search lists, one could utilize a collaborative search strategy, in which devices also send their known neighbours to reduce the number of devices that have to be searched on each device.

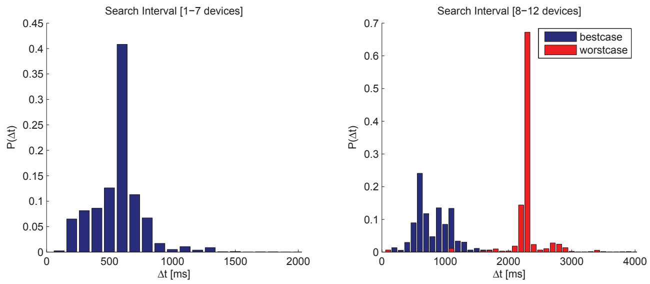

Figure 2. Search Interval Distribution. Left: when searched for 1-7 devices, one or 12 devices present. Right: when searched for 8-12 devices, bestcase: 12 devices present; worstcase: only one device present. Device ID's were transmitted with 6 Hz.

Search Interval

The maximum search interval SI is the time between two searches of the same device. Fixing the channel frequency, the search interval is dependent on the number of channels used for searching, as well as the length of the search list. In the best case, all devices that are searched are also discovered and no channel is blocked until a search timeout occurs. The search interval is then given by:

$$SI(x) = \lceil \frac{x}{\text{\# search channels}} \rceil * SI(1), \qquad (1)$$

where x is the number of searched devices, $\lceil . \rceil$ is the integer ceiling function and $SI(1)$ is the maximum time that it takes to search one present device. In the worst case, only one of the searched devices is present and timeouts will occur. The search interval is then given by:

$$SI(x) = (\lceil \frac{x}{\text{\# search channels}} \rceil - 1) * t_{st} + SI(1), \qquad (2)$$

where t_{st} is the time of the search timeout.

To evaluate the search interval in best and worst case scenarios, we measured the search interval using seven search channels. In the best case, 12 devices were present and continuously transmitted their device ID's six times per second. In the worst case only 1 device was present and transmitted its device ID. For both cases, we repeatedly measured the search interval over a period of ten minutes increasing each time the number of devices to search for from 1 to 12. For each configuration, we randomly sampled 250 search intervals, totaling to 6000 search intervals in our analysis.

With seven search channels, up to seven devices can be searched in parallel and worst and best case search intervals do not differ. The distribution of measured search intervals is shown in the left of Figure 2. On average devices are found again within 600 ms and within $SI(1) = 1500$ ms at most. We therefore, set the search timeout t_{st} conservatively to 2000 ms. In case that more than seven devices are searched the search interval will depend on the number of present devices. In the best case, all devices that are searched are present, in the worst case, only the device at the end of the search list is present, and the search timer times out at least once until the device is found. The distribution of measured search intervals is shown in the right of Figure 2.

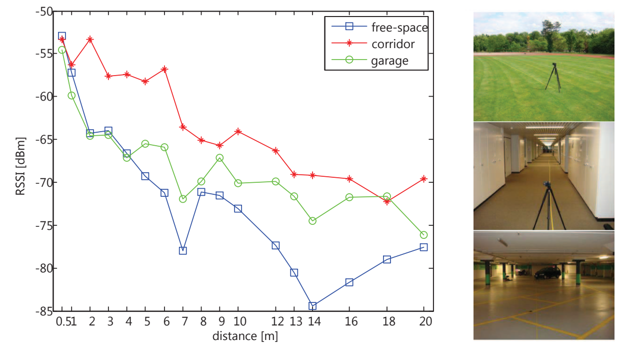

Figure 3. Average relationship between RSSI and distance in three different environments as measured between two ANT-enabled smartphones. Transmit power was set to 0 dBm.

Search Distance

The free-space path loss is proportional to the square of the distance between the transmitter and receiver. However, the received signal strength (RSS) is generally not proportional to the distance due to the influence of other parameters such as variation of transceivers, antenna orientation, height of transceivers and other environmental factors [12, 14, 13]. To illustrate the problem, we have measured the RSSI for different distances between receiver and transmitter in three different environments. Figure 3 shows the average RSSI measured at different receiver-transmitter distances. As can be seen, RSSI does not monotonously decrease with increasing distance. Because of the nonlinear effects of RSSI, we decided to ignore the RSSI level and to consider persons to be in proximity if messages arrive at all.

In order to reduce maximum communication distance, we set the transmit power as low as possible to -20 dBm. With this setting, we tested the maximum distance at which messages are still received from the transmitting device in different scenarios. In the distance experiments, two persons hold the smartphone in the hand in front of their upper body and either faced each other, turned their backs to each other, or looked in the same direction, so that one person looked at the back of the other person. The tests were conducted in different environments: a office corridor with metal cupboards to the left and right, a garage with pillars, a foyer of a university building and outside in an alley between two buildings. In all cases, there were no other objects between the two persons. On average, we observed about 1 m range for back-to-back, 1 m to 4 m range for face-to-back, and 9 m to 20 m range for face-to-face configurations. In our targeted application of monitoring sub-groups of firefighters during missions these maximum distance ranges seem reasonable as for example troop members usually work within reach holding on to each other for safety reasons. Firefighters that operate outside the building can be considered to be part of one sub-group as long as they can see each other and are within 20 m distance.

GROUP CLUSTERING

Our approach to detect moving groups over time from the recorded proximity data is illustrated in Figure 4. Like [16], the approach consists of two steps: first, the proximity data is

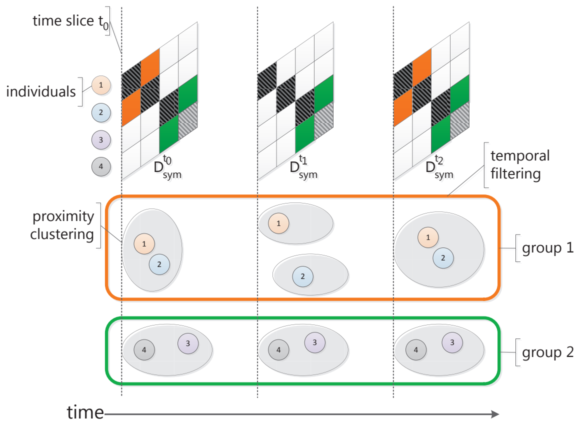

Figure 4. Group clustering: At each time step the proximity matrix indicates who is in proximity to whom and groups are detected based on the single-link criterion. The results of each time step are then smoothed by a temporal filter. In the example two groups are present.

clustered independently for each time slice; second, the clustering output is smoothed using temporal filtering.

Group Clustering

For each time slice t, the binary elements of the proximity matrix D^t_{ij} indicate if device i received any message from device j within the last period P. Because we are not interested in directed links, we symmetrize the proximity matrix by adding the transpose

$$D^t_{sym} = D^t + (D^t)^T. \tag{3}$$

Based on the symmetrized proximity matrix each time slice is clustered by the single-link criterion, so that all connected pairs are merged to one cluster using Algorithm 1. In principle, for each of the N individuals i, one cluster is created containing i and all it's neighbours. In case that there exists already another cluster that contains at least one of the current members the two clusters are merged.

Considering Height Levels

Using only radio based proximity information might lead to individuals on different height levels to be clustered into one group. However, depending on the goal of the clustering, this might not be desired. To consider height levels, we additionally take the absolute atmospheric pressure difference APD^t_{ij} between individuals i and j at time step t into account. If APD^t_{ij} is smaller a threshold value τ_{height}, individuals i and j are considered to be on the same level, which is expressed by $L^t_{ij} = [APD_{ij} < \tau_{height}]$. If height differences should be considered during clustering, each element of the proximity matrix D^t has to be multiplied with the corresponding element of L^t at each time step t.

$$D^t_{sym} = D^t \circ L^t + (D^t \circ L^t)^T, \tag{4}$$

where $\circ$ denotes element-wise matrix multiplication.

Temporal Smoothing

As we are interested in clusters that persist for at least τ time steps, we smooth the individual clusterings by applying a temporal filter as suggested in [16]. At each time step,

Algorithm 1 clustering of time slice L^t

function CLUSTER(L^t)
  $C^t = \emptyset$
  for $i = 1 : N$ **do**
    $nc = i$
    for $j = i + 1 : N$ **do**
      if L^t_{ij} **then**
        $nc = nc \cup j$
      end if
    end for
    C^t =MERGE($clusters, nc$)
  end for
  return C^t
end function
function MERGE($clusters, nc$)
  $mc = \emptyset$
  for $c \in cluster$ **do**
    if $c \cap nc = \emptyset$ **then**
      $mc = \{mc, c\}$
    else
      $mc = \{mc, c \cup nc\}$
    end if
  end for
  return mc
end function

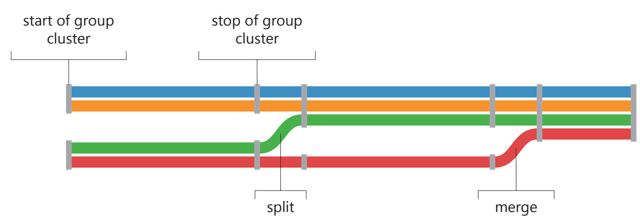

Figure 5. Visualization of group clustering over time in form of a narrative chart. Individuals that are in proximity are represented by closely spaced colored lines. Groups of lines that are apart from another represent groups of individuals not in proximity.

a group cluster is either an active or a potential cluster. A group cluster is considered an active cluster, if it persisted for at least τ time steps and a potential cluster otherwise. Only if a potential cluster has lasted longer than τ time steps, it is promoted to an active cluster. In case that an active cluster has not been detected in any of the previous δ time steps it is deleted. At each time step the active clusters are taken as the smoothed output. If at any time step a person is not assigned to an active cluster, the clustering of the previous time step is used instead.

Visualization

Based on the idea of narrative charts[2] which display when characters in a movie appear together, we visualize the proximity of group members over time. An example of a narrative chart is presented in Figure 5. Each individual is represented by one line of different color. Individuals who form a group cluster are represented by lines which are close together. Each

[2] `http://xkcd.com/657`

Figure 6. Training scenario. Firefighters had to enter through the roof window and navigate blindly to the fire below a spiral staircase. On the way to the fire a dummy person had to be found and rescued.

start and end of a group is represented by a vertical bar. When individuals change groups, splits and merges occur. Because we do not measure distance between individuals, space between lines does not correspond directly to distance but indicates different groups of individuals.

FIREFIGHTING EXPERIMENT

In close collaboration with the a professional fire brigade, we examined how our group proximity clustering methods perform in training sessions of professional firefighters and how the proximity dynamics can be used to analyse the training sessions. In this section, we will explain the conducted experiment and describe the training scenario.

The experiment took place in a fire simulation building in which a variety of incidents, ranging from kitchen fires to burning cars in the garage, can be staged. During trainings, firefighters are confronted with real fires, extreme heat, high humidity and thick smoke that severely restricts visibility. Together with the training instructors, we designed a non-standard training scenario with increased difficulty to ensure that different teams would not perform equally well.

Each firefighter has a specific role which is fixed to the seating position in the firetrucks. The incident commander (IC) leads the operation and is in charge. On-site, the driver of the turntable ladder (TL) is responsible for operating the ladder, whereas the driver of the fire truck becomes the engineer (E) who operates the water pumps. The engineer keeps track of which firefighter uses the self contained breathing apparatus (SCBA). All other firefighters are part of a troop. The two troops are led by a troop leader (T1a,T2a) and contain one or two additional firefighters (T1b, T1c, T2b, T2c).

In Figure 6 the training scenario is illustrated. In the scenario, a fire on the third floor of the training building had to be put out. In the beginning of the training mission, the hose was prepared, the engineer connected the fire hose to the hydrant and the first troop was transported with the turntable ladder to the roof window which was the only entrance point allowed (see 1,2). Once the troop was inside the building (see 3), the firefighters had to fight against the heat of the fire maneuvering from the fourth floor to the third floor (see 4). On the way towards the fire, a non expected dummy person had to be found and rescued. As the troop leader was not informed of any missing person, he had to decide how to correspond to the new situation. Only after the dummy person was safe the fire should have been extinguished, either be the first troop or by an ordered second troop (see 5,6).

EVALUATION

First, we will qualitatively evaluate the clustering result of one training mission to investigate where the group clustering performs well and where the results do not match the ground truth. Second, we will quantitatively compare the clustering solutions to the ground truth in terms of clustering accuracy.

We successfully recorded 16 training runs of the same scenario and in total 51 professional firefighters took part in our experiment. The duration of the training missions ranged from 10 to 16 minutes. All training runs were videotaped with two regular and one thermographic camera.

In all evaluations, we used the following parameter settings: The slice period P was set to 5 s. For the temporal smoothing, we set the parameter τ to 10 s and δ to 5 s. We set the parameter τ_{height} to 1 hPa to consider firefighters with a height difference of less than 8 m to work on the same height level.

Qualitative Analysis

Figure 7 shows how the group structure changes over time within one training mission. Presented are two visualizations, the first one represents the clustering results when only ANT-based proximity information was used, whereas the second one represents the clustering results when ANT-based proximity information was combined with atmospheric pressure signals. The pictures on top of the graphs in Figure 7 show important steps of the training mission.

We first look at how well the two clustering solutions capture mission operations. At the start of the mission, two groups are identified which correspond to the seating in the fire trucks.

At (a) T2c is on his own while running around the house in order familiarize himself with the situation behind. At (1) all firefighters are in-sight to each other and form one group when they are preparing the turntable ladder and the quick-attack hose. At (2) the first troop is brought upwards with the turntable ladder which can be seen in the two clustering results as the first troop is shown to split (T1a,T1b,T1c are seperated from the rest). At (d) the two clustering solutions are now becoming different. As can be seen in picture (d), one of the troop members turns towards the firefighters on ground and as such connects the two separate groups. As a consequence the two groups will be joined if the clustering is only based on ANT-proximity. At (3) troop members T1a and T1b enter the building through the roof window and begin to navigate which can be seen in both clustering solutions (4). Around (5) the second troop climbs the turntable ladder. As there is still a connection to the other firefigthers outside the building this cannot be seen in the first clustering, but only in the second one which considers the height difference. At (7) T2a and T2b enter the building and because there is no connection to other firefighters this can also be seen in the first clustering solution. This split is seen a few time steps later in the first clustering solution due to the temporal filtering.

To evaluate in which situations, the group clustering works well, we now look at the splits and merges of E and T2c which are equal in both clustering solutions. At (b) and (c) E is shown to be separate from the other firefighters, this is because the line-of-sight to the other firefighters is blocked by some rocks when connecting the hose to the hydrant. At (e) and (f) E is in proximity to IC and TL when standing left to the fire truck, whereas E is alone at (g),(h),(i) and (j) when he is behind the fire truck operating the machinery. Turning to T2c, it appears that T2c is on his own at (e) and (f), but from the corresponding pictures, we see that he is in fact behind the turntable ladder but turned his body away from the other firefighters. At (g) and (j) T2c turned his body more towards the incident commander at the left side of the picture and as a consequence is in a group with IC and TL.

Summarizing the qualitative analysis, we find that the clustering solution which combines ANT-based proximity with pressure signals is better suited to show how a mission evolves over time as mission relevant information is presented clearer. From the proximity graph, one can easily identify important mission events such as when the turntable ladder reached final position and when and for how long a troop is operating levels above ground. However, also from the ANT-based proximity clustering one can infer when and for how long a troop is inside the building. From the examples of E we saw, that the group clustering overall corresponds well to the in-sight criterion, however, in the case of T2c, we have seen that a firefighter can be in-sight to other firefighters, but because he blocks the radio signals with his body he is not detected to be in proximity with others. The effect that the body blocks the radio signals became also apparent at (d) when the troop used the turntable ladder facing the building.

Quantitative Analysis

For a quantitative analysis of the presented group clustering algorithms, we calculate the accuracy metrics proposed in [16] and evaluate how well the group clustering results match manually annotated ground truth.

Accuracy Metrics

Let the set of individuals be defined as $I = \{1, .., N\}$ with N being the total number of individuals. Further, let a clustering at time step t be described by the partition C^t and $|C^t|$ be the number of clusters at time step $t \in \{1, .., T\}$ with total time steps T. A particular cluster is indexed by $C^t(i)$. Clusters of the ground truth and the algorithm are indicated by C^t_{GT} and C^t_A, respectively.

The Number of Groups Detected Accuracy (NGDA) expresses the fraction of time steps in which the algorithm detects the same number of group clusters N_c as are present in the ground truth:

$$NGDA = \frac{1}{T}\sum_{t}^{T}[|C^t_{GT}| = |C^t_A|] \tag{5}$$

To measure how far of the algorithm is, we also calculate the Average Number of Groups Detected Error (ANGDE) as the average over all time steps of the absolute difference between the number of groups in the ground truth and as detected by the algorithms:

$$ANGDE = \frac{1}{T}\sum_{t=1}^{T}||C^t_{GT}| - |C^t_A|| \tag{6}$$

The Average Group Assignment Accuracy (AGAA) expresses how well individuals are assigned to the correct group cluster on average over all time steps. For each time step, we calculate the number of correctly assigned individuals c^t as following: for each ground truth cluster, the predicted cluster with the highest number of shared group members is searched and the number of shared group members is added to the number of correctly assigned individuals. In formula:

$$c^t = \sum_{i=1}^{|C^t_{GT}|}\max_j |C^t_{GT}(i) \cap C^t_A(j)|. \tag{7}$$

AGAA is then given by:

$$AGAA = \frac{\sum_{t=1}^{T} c^t}{N * T}. \tag{8}$$

Ground Truth Annotation

In order to evaluate our clustering algorithm, we manually labeled the video recordings of six complete training runs in two different ways. The first ground truth places the focus on being in-sight to each other and we consider two firefighters to be in proximity when at least one of them can see the other and no object blocks the line-of-sight. The motivation for the first ground truth lies in the fact that implicit coordination requires to see or hear each other so that a firefighter can overview the actions of his peers. With the second ground truth we incorporate the height level that a firefighter works on, that is we distinguish if a firefighter is on ground level

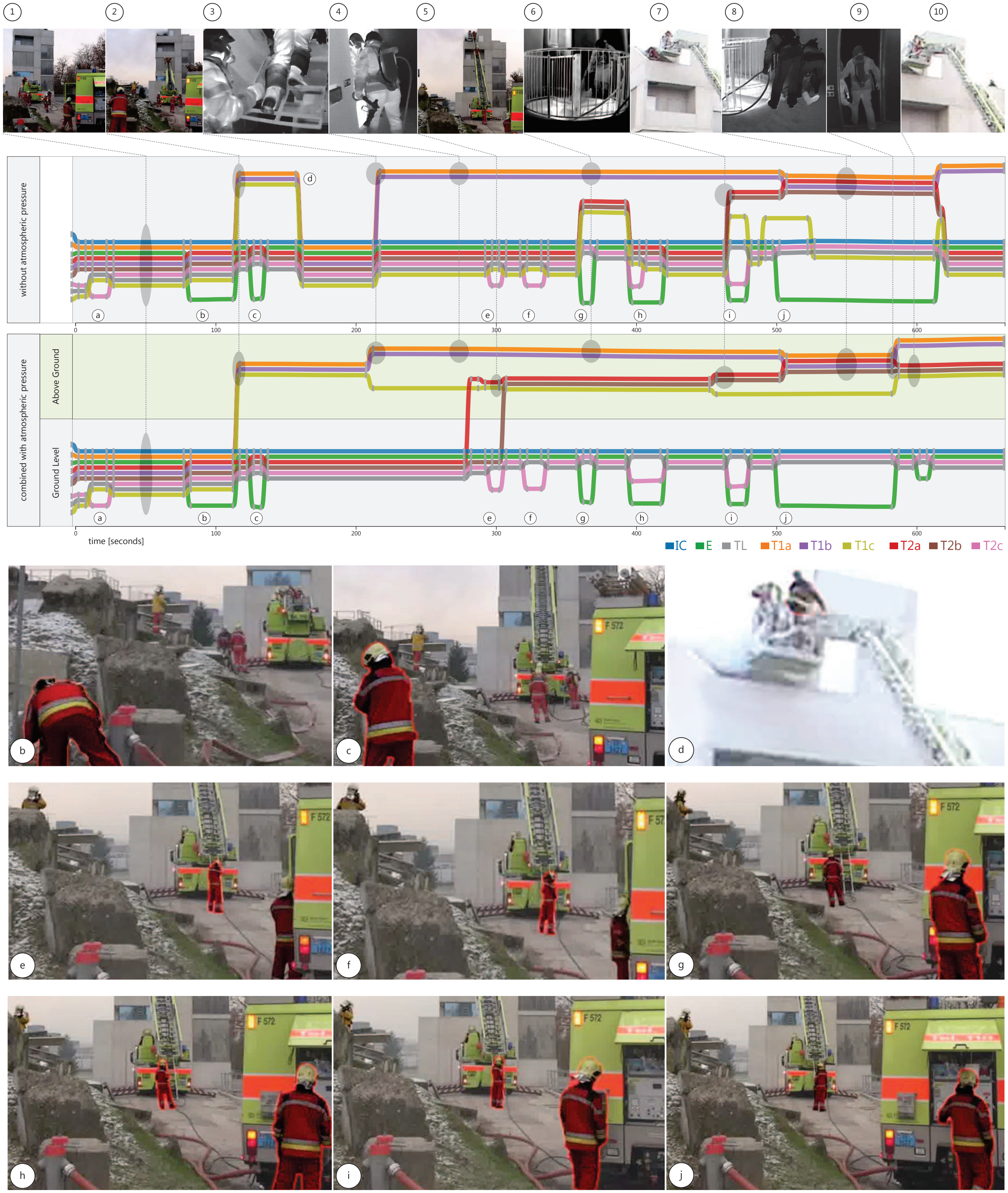

Figure 7. Visualization of the group clustering of a firefighting training mission. Presented are two clustering results. Top: only ANT-based proximity was used. Bottom: ANT-based proximity was combined with atmospheric pressure signals to also consider height differences of firefighters.

	filter	NGDA [%]	ANGDE	AGAA [%]
ANT-based	no	37 (12)	0.74 (0.11)	80 (6)
proximity (Eq. 3)	yes	37 (14)	0.73 (0.13)	80 (6)
incl. atmospheric	no	64 (15)	0.38 (0.17)	95 (4)
pressure (Eq. 4)	yes	66 (14)	0.35 (0.14)	95 (3)

Table 1. Accuracy of group clustering algorithms. Mean and standard deviation (in brackets) across six firefighting teams performing a training scenario.

or operates at the top of the turntable ladder or in the building on floors above ground level. Consequently, a firefighter who is on ground level and can see the firefighter on top of the turntable ladder is now not considered to be in proximity with the firefighter on top. Thus, the focus is placed on mission operations as this ground truth additionally captures who is above ground levels.

Group Cluster Accuracy

We applied the group clustering to six annotated runs of the training scenario totaling to 79 minutes of training mission data. The mean and standard deviation of the accuracy metrics across the training missions of six teams are summarized in Table 1. On average the proximity based clustering algorithm detects the correct number of groups in 37% of all time steps. In terms of NGDA the performance of the group proximity clustering appears to be low, however, one should keep in mind that NGDA is a rather hard accuracy metric, as already the misassignment of one individual results in an error at the corresponding time step, even if all other individuals are assigned correctly. From the ANGDE, we conclude that on average the algorithm is close to the number of groups present in the ground truth, meaning that the algorithm detects on average one group too much or too less. When proximity information is combined with atmospheric pressure, we see that the performance of the clustering algorithm increases. In two-thirds of the time, the correct number of groups is detected and individuals are assigned to the correct cluster with an AGAA of 95%. Temporal smoothing did not increase the results when only proximity information was used for the clustering, but it slightly increased clustering performance when additional height information was utilized.

CONCLUSION

We presented a methodology to cluster moving groups over time from radio-based proximity data. Relying on ANT-based radio messages instead of Bluetooth scans enabled us to scan nearby devices at a rate of up to 50 times faster than with commonly used Bluetooth scans. The increased time resolution allowed us to capture group proximity dynamics of firefighting teams. Further, we presented how group proximity dynamics of firefighting teams can be visualized in form of narrative charts showing which firefighters were when in proximity to each other. This compact representation of mission operations enables incident commander or training instructor to easily inspect how a mission evolved over time and to pinpoint important mission events. Moreover, we evaluated our group clustering algorithm on real-life data of six professional firefighting teams performing a training scenario in a fire simulation building. When compared to manually annotated ground truth, our ANT-based algorithm correctly assigned firefighters to the correct group in 80% of the time. When ANT-based proximity information was combined with atmospheric pressure signals, the average group assignment accuracy (AGAA) increased to 95%. In future work, we will analyse the group proximity graphs of different performing firefighting teams.

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REFERENCES

1. FIRE - Fire Information and Rescue Equipment. `http://fire.me.berkeley.edu/`.
2. NIST Smart Firefighting Project. `http://www.nist.gov/el/fire_research/firetech/project_sff.cfm`.
3. ProeTEX - Advanced e-textiles for firefighters and civilian victims. `http://www.proetex.org`.
4. ProFiTex - Advanced Protective Firefighting Equipment. `https://www.project-profitex.eu/`.
5. Wear IT at work. `http://www.wearitatwork.com/`.
6. Do, T. M. T., and Gatica-Perez, D. Human interaction discovery in smartphone proximity networks. *Personal and Ubiquitous Computing* (2011).
7. Eagle, N., and (Sandy) Pentland, A. Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing* (2005).
8. Fischer, C., and Gellersen, H. Location and Navigation Support for Emergency Responders: A Survey. *Pervasive Computing* (2010).
9. Jensen, C., Lin, D., and Ooi, B. Continuous clustering of moving objects. *Knowledge and Data Engineering* (2007).
10. Kalnis, P., Mamoulis, N., and Bakiras, S. On discovering moving clusters in spatio-temporal data. *Advances in Spatial and Temporal Databases* (2005).
11. Li, Y., Han, J., and Yang, J. Clustering moving objects. In *Proc. SIGKDD* (2004).
12. Lymberopoulos, D., Lindsey, Q., and Savvides, A. An empirical characterization of radio signal strength variability in 3-d ieee 802.15. 4 networks using monopole antennas. *Wireless Sensor Networks* (2006).
13. Srinivasan, K., Dutta, P., Tavakoli, A., and Levis, P. An empirical study of low-power wireless. *ACM Transactions on Sensor Networks* (2010).
14. Stoyanova, T., Kerasiotis, F., Prayati, A., and Papadopoulos, G. Evaluation of impact factors on RSS accuracy for localization andtracking applications in sensor networks. *Telecommunication Systems* (2009).
15. Wilson, J., Bhargava, V., Redfern, a., and Wright, P. A Wireless Sensor Network and Incident Command Interface for Urban Firefighting. In *Proc. MobiQuitous* (2007).
16. Wirz, M., Kjaergaard, M. B., Feese, S., Schläpfer, P., Roggen, D., and Tröster, G. Towards an online detection of pedestrian flocks in urban canyons by smoothed spatio-temporal clustering of gps trajectories. In *Proc. LBSN* (2011).